# ESTIMATION OF PRODUCTION TIME BY REGRESSION AND NEURAL NETWORKS

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## Abstract

*The estimation of production times will be the necessary future basis for cost estimation, cost reduction or TCE (Total Cost Estimation). An experienced process planner usually makes decisions based on comprehensive data without breaking it down into individual parameters. So, as the first phase it was necessary to establish a technological knowledge base, define features of the 2D drawing (independent variables), possible dependent variables, size and criteria for sample homogenization (principles of group technology) for carrying out analysis of variance and regression analysis. The second phase in the research was to investigate the possibility for easy automatic, direct finding and applying 3D features of an axial symmetric product to the regression model. The third phase in the research was to investigate the possibility for the application of neural networks in production time estimation and to compare the 224 results between the regression models and neural network models. The most important characteristic of our approach presented in this paper is estimation of production times using group technology, regression analysis and neural networks.*

**Keywords**: stepwise multiple linear regression, group technology, knowledge base, production time, neural networks, TCE

## 1. INTRODUCTION

An experienced process planner usually makes decisions based on comprehensive data without breaking it down into individual parameters. So, as the *first phase* it was necessary to establish a technological knowledge base, define features of 2D drawings (independent variables), possible dependent variables, size and criteria for sample homogenization (principles of group technology) for carrying out analysis of variance and regression analysis. The *second phase* in the research was to investigate the possibility for easy automatic, direct finding and applying 3D features of an axial symmetric product to the regression model. The defined requirements resulted in the development of the procedure for retrieval of parameters from the 3D model with a low level of subjectivity, a very fast and reliable process via CAD report to the regression model. The *third phase* in the research was to investigate the possibility for the application of neural networks in production time estimation and to compare the results between the regression models and neural network models. As it can be seen from the list of references, different approaches are used for data retrieval from AD (STEP) [1], integration of CAPP, CAD/CAM and business activities [2], development of database system of mechanical components [3,4], and integrated product engineering [5] for costs estimation and rapid cost estimation [6], application of neural networks in estimation of production times [7], connection from CAPP, CAD, CAM; DFx to DFA through product development [8] etc. The most important characteristic of our approach presented in this paper is estimation of production times using group technology, regression analysis and neural networks [7], [9, 10, and 11].

## 2. DRAWING FEATURES AND TECHNOLOGICAL DATABASE FOR PRODUCTION TIME ESTIMATION

Very frequently (especially in the case of Small and Medium Enterprises - SMEs) it is necessary to respond quickly to some important requests for offers, generated for individual or batch production, for example in the case of:

1) a great number of requested offers for manufacturing of products at once,

2) small batches that are very rarely repeated,
3) frequent changes of priorities during production,
4) short deadlines for delivery,
5) market demands for bringing prices of individual or batch production close to the prices of mass production, etc.

It must be noted that technological knowledge and speed of process planning are often more important than the technological level of equipment, skills and knowledge of people who implement the technology. So, very often in practice we can be faced with the following:

a) A great amount of time spent on planning of the technological process for a product without any specific contract being made concerning the order for manufacturing of the product,
b) Signing of a contract without estimated precise production times/costs necessary for product manufacturing and realization in accordance with contracted production.

Technological processes are basically based upon product drawings with adequately defined dimensions, tolerances (dimensional and geometrical), surface roughness, batch size, shape and kind of material, heat treatment, requested delivery, disposable equipment, tools, etc. At the same time, process plans are primarily result of the planner's experience, intuition and decision support. A process planner can establish possible connections between drawing features and necessary production times for products manufacturing. The fundamental idea in the approach [10, 11] to production time estimation is investigation of the existence of some kind of relationship between the shape and data from the drawing and the process type, process sequencing, primary process, way of clamping, selection of tools, machine tools, production times, etc. As one of the *first steps in our project research*, we defined possible shapes of raw material and 30 potential basic technological processes.

## 3. DEVELOPMENT OF STEPWISE LINEAR MULTIPLE REGRESSIONS

A desirable level of generalization in regression analysis will be an important indicator for the quality of regression equation. One of the most important problems was the process of homogenization of the sample of products. Adequate method for this action was one of the methods of group technology. For the sample of real products (420 parts) and considered features, we created, as a result of our investigation and step multiple linear regression (in previous research and papers), 8 regression equations for different groups of parts with different number and kind of independent variables. So, we can see for different values of parts' features (independent variables), the values for the estimation of production times (dependent variables). However, the results of process optimization for 8 regression equations by genetic algorithm cannot be applied in real production. Logical operators during query process in database Access were very helpful in the process of homogenization of the sample of products.

As the result of previous research, sample homogenization, classifier selection and stepwise multiple linear regression, we obtained: 7 independent selected variables, basic sample of 320 parts, constraints for data parts, 8 regression equations, percentage of explained effects, relative error (7-30%), etc. (Table 1). The lowest relative error 8.01% (Table 2, for grinded discs, AC102 No. 5) and the highest index of determination $r^2 = 0.9851$ for the grinded discs group are the consequence of the simultaneous action of logical operators (round bars, discs and fine machining – i.e. diameter tolerance better than IT7). Thus, with the simultaneous action of several operators, a lower scattering of production time values has been achieved, i.e. better homogeneity of the created group.

Since there was too great subjective influence of workers in the process of filling in the values of independent variables, we continued with investigation in the 3D area. The question was how to get automatically the 3D features from CAD application (CATIA, PRO/E) in the application for developed regression equations and avoid thus this subjectivity factor.

The *second phase* in the research was the investigation of the possibility for easy automatic, direct retrieval of 3D features of the considered axial symmetric product into the regression model. The defined requirement resulted in the development of the process for the transfer of parameters from 3D models with a low level of subjectivity. It is a very fast and reliable process via CAD report to the regression model [12].

As a possibility to improve our precision in estimating the production times of ‘new unknown products’, in the next phase of our research we chose a neural network to compare the validity of the two methods: linear multiple stepwise regression and neural network model.

Table 1. Explanation of the meaning of used symbols

| Symbol | Physical unit | Meaning of the symbol |
|---|---|---|
| $f_{ea}$ | - | Features of 3D |
| K | - | Coefficient of time |
| $K_s$ | - | All dimension lines |
| $R^2$ | - | Index of determination |
| t | (min) | Machining time |
| $x_1$ | (IT) | Order of tolerance outside diameter |
| $x_2$ | (mm) | Outside diameter of material |
| $x_4$ | (mm) | Width of material |
| $x_6$ | (mm) | Length of material |
| $x_8$ | Class h | Roughness of open areas |
| $x_9$ | HRc | Hardness of product |
| $x_{10}$ | (mm) | Outside diameter of product |
| $x_{11}$ | (mm) | Inside diameter of product |
| $x_{15}$ | - | Number of product perspectives |
| $x_{16}$ | - | Number of descriptions of product |
| $x_{18}$ | - | Number of location marks (geometry) |
| $x_{19}$ | - | Number of dimension line tolerances |
| $x_{20}$ | - | Number of special dimension lines |
| $x_{21}$ | - | Number of usual dimension lines |
| $x_{22}$ | (1/class) | Roughness request Ra |
| $x_{23}$ | (1/mm) | Location request (geometry) |
| $x_{24}$ | (1/mm) | Dimension request |
| $x_{25}$ | (1/IT) | Diameter request |
| $x_{26}$ | ($mm^2$) | Area of sketch |
| $x_{29}$ | ($N/mm^2$) | Ultimate tensile strength of material |
| $x_{30}$ | ($m^2$) | Requested area of sketch |
| $x_{31}$ | - | Mass strength of material |
| $x_{32}$ | (mm) | Thickness wall of products |
| $x_{33}$ | - | Ratio of diameter and length |
| $x_{39}$ | - | Number of all dimension lines |
| $x_{40}$ | - | Product complexity |
| $x_{42}$ | (Class h) | Difference in roughness |
| $x_{43}$ | ($dm^2$) | Difference in superficial areas of material |
| $x_{44}$ | ($cm^3$) | Volume of material |
| $x_{45}$ | (kg) | Mass of material |
| $x_{46}$ | (mm) | Difference in outside diameters |
| $x_{47}$ | (mm) | Difference in outside diameter of products |
| $x_{49}$ | (mm) | Difference in thicknesses |
| $x_{50}$ | (mm) | Difference in lengths |
| Y | (min) | Production time |

## 4. NEURAL NETWORK MODEL

Artificial neural networks (*ANN*) are inspired by the biological neural system and its ability to learn through examples. Instead of following a group of well defined rules specified by the user, neural networks learn through intrinsic rules obtained from presented samples. The most commonly used *ANN* architecture is the multilayer *backpropagation neural network*. Backpropagation was created by generalizing the *Widrow-Hoff* learning rule to multiple-layer networks and nonlinear differentiable transfer functions [14]. Input vectors and the corresponding target vectors are used to train the network until it can approximate a function, associate input vectors with specific output vectors. Standard backpropagation is a gradient descent algorithm, as is the *Widrow-Hoff* learning rule, in which the network weights are moved along the negative of the gradient of the performance function.

Table 2. Presentation of created regression equations

| No | Shape of product representative of product group | Regression equations | Index of determ. $R^2$ | Relative error [%] | Comment on regression equation |
|---|---|---|---|---|---|
| 1 | Whole sample **A0000** | $t = -11.69 + 16.95x_{45} + 1.22x_{40} + 0.54x_{47} + 127.47x_{22} - 3.24x_{18} + 0.15x_{32} + 0.03x_{6}$ | 0.736552 | 30.74 | Model is developed with procedure in advance. Three independent variables are omitted $x_8$, $x_{19}$ and $x_{33}$. |
| 2 | Round bars **A00B1** | $t = 55.47 + 22.43x_{45} + 1.162x_{40} + 0.43x_{11} + 1.61x_{50} - 5.41x_{8} - 3.26x_{18} + 1.78x_{42}$ | 0.74285 | 30.95 | Model is developed with procedure in advance.Two independent variables are omitted $x_1$ and $x_{26}$. |
| 3 | Shafts **AB101** | $t = 6.13 + 0.83x_{2} + 1.27x_{39} - 3.30x_{8} + 5.51x_{46} - 6.86x_{18} + 0.09x_{6} + 124.33x_{22}$ | 0.807626 | 25.90 | Model covers more narrow field of rotational parts. It gives better results than No.2. |
| 4 | Discs **AB1C1** | $t = -5.17 + 0.73x_{47} + 0.93x_{40} + 5.25x_{20} + 0.52x_{24} + 139.11x_{30} + 0.23x_{32} - 0.51x_{33}$ | 0.809405 | 24.24 | Simillar results as in No.3. |
| 5 | Discs-with fine machining **AC102** | $t = -60.78 + 0.59x_{47} + 047x_{9} + 0.74x_{1} + 0.25x_{10} + 0.84x_{39} + 291.07x_{25} + 5.9x_{15}$ | 0.985057 | 8.01 | Model covers more narrow field of rotational parts. It gives better results than all the previous models. |
| 6 | Rotational parts **AB103** | $t = -37.11 + 0.94x_{40} + 0.03x_{29} + 319.22x_{26} + 0.13x_{23} + 114.67x_{43} - 80.98x_{45} - 0.46x_{6}$ | 0.893321 | 27.06 | Model is better than No. 2 as a result of higher degree of homogenization of data. Solution is better with omitted variables $x_2$ and included variables $x_6$, $x_{23}$, $x_{43}$ and $x_{45}$. |
| 7 | Flat bars **A0004** | $t = -10.96 + 0.58x_{40} + 34.50x_{45} + 218.42x_{22} - 5.48x_{50} + 185.03x_{26} + 0.39x_{9} - 0.50x_{49}$ | 0.900332 | 15.92 | Constraints are greater for all variables so results are better. Narrow field of homogenization. |
| 8 | Sheet metals **A0005** | $t = 0.47 + 1.27x_{40} + 137.45x_{45} - 13.23x_{43} - 0.70x_{43} + 0.28x4 + 0.05x_{6} + 3.91x_{16}$ | 0.900823 | 24.04 | Model is characterized with the presence of complex variables $x_{40}$, $x_{43}$, $x_{45}$ |

The term *backpropagation* refers to the manner in which the gradient is computed for nonlinear multilayer networks. *Backpropagation* neural networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. There are numerous variations of the basic algorithm that are based on other standard optimization techniques, such as conjugate gradient and Newton methods. The one used in this paper is the *feedforward backpropagation* training algorithm designed to minimize the *mean square error* (*MSE*) between the actual (estimation) output ($a$, $A$) and the desired (target) output ($d$, $T$).

Figure 1. shows the principle of the *feedforward backpropagation* training algorithm, where: $V_{ij}$ - weight between the input layer and the hidden layer, $W_{jk}$ - weight between the hidden layer and the output layer, $X_i$ - input signals, i - number of neurons of the input layer, I - number of inputs of neuron j in the hidden layer, $Y_j$ - output of the hidden neurons, j - number of neurons of the hidden layer, J - number of inputs of neuron k in the output layer, $Y_k$ - output signals, k - number of neurons of the output layer. For the estimation of performance of the learning algorithm in solving the specified task, performance index was defined. Performance index enabled comparison of the applied neural network algorithm with other learning algorithms. The most frequent performance index is the normalized root mean square error – *NRMSE* .

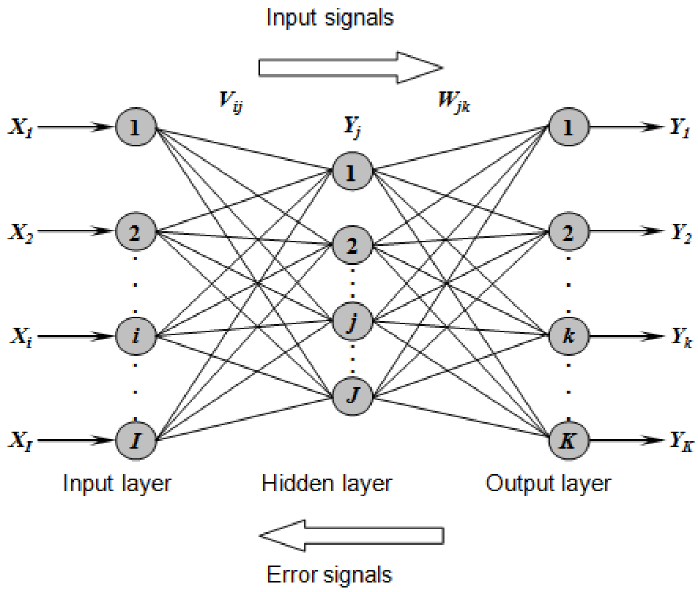



Figure 1. Principle of the feedforward backpropagation training algorithm

Where: $N$ is the total number of patterns, $d_n$ is the desired (target, $T$) outputs, $a_n$ is the actual (estimation, $A$) outputs, $\sigma_{dn}$ is the standard deviation.

$$NRMSE = \frac{\sqrt{\frac{\sum_{n=1}^{N}(d_n - a_n)^2}{N}}}{\sigma_{d_n}} \qquad \sigma_{d_n} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(d_n - \bar{d}\right)^2} \qquad \bar{d} = \frac{1}{N}\sum_{n=1}^{N} d_n \tag{1}$$

## 5. EXPERIMENTAL RESULTS

As a better method for solving the problem of production time estimation, we proposed a three-layer backprogation neural network the simplified structure of which is shown in Figure 2.

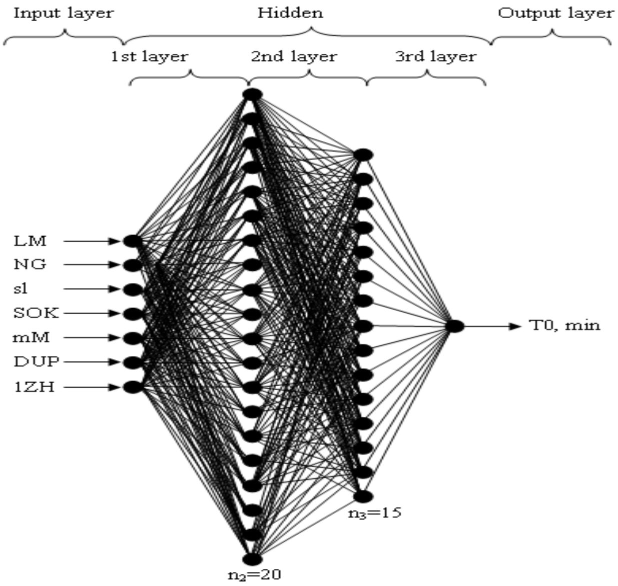
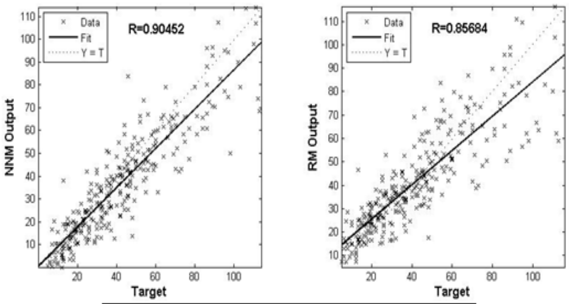
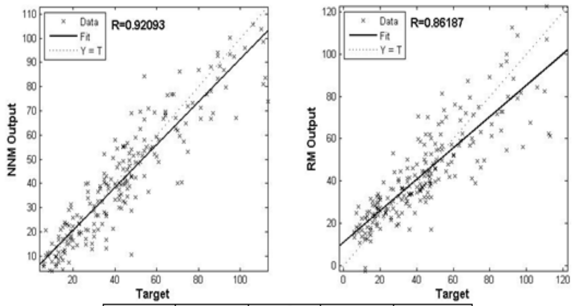



Figure 2. Simplified model of the used neural network of A0000 model

Presented input parameters (LM, NG, sl, SOK, mM, DUP, lZH) refer to the model A0000. Output parameter (TO) is the estimate of time in minutes. Parameters $n_2$=20 and $n_3$=15 represent the number of neurons in the second and third layer of the network. Between the layers the following transfer functions are applied: *tansig-tansig-purelin*. Data important for neural network training are: Performance goal: 0.0001, Learning rate-0.01, Ratio to increase learning rate-0.5, Maximum performance increase: 1.04, Maximum performance gradient: 1e-10, Momentum constant: 0.9, Number of layers: 3, Number of neurons: 20-15-1, Transfer functions: tansig-tansig-purelin, Number of epoch to train: 15000. For neural network training the available experimental data are divided in three sets: training set (70%), validating set (15%), and testing set (15%). The same model of experimental data division is applied to all models. The following parameters are selected as *key performance indexes* of the neural network model (*NNM*) in relation to the regression model (*RM*): R (correlation coefficient), $R^2$ (determination coefficient), RMSE (root mean square error) and NRMSE (normalized root mean square error). In Figure 3. through Figure 6. for each experimental model the graphical presentation of parameter R values and tabulated values of parameters R, $R^2$, RMSE and NRMSE are given.

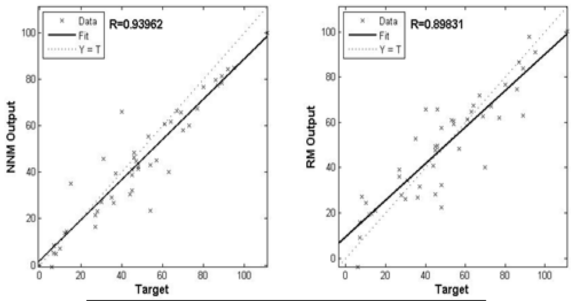



| | R | $R^2$ | RMSE | NRMSE |
|---|---|---|---|---|
| NNM | 0.9045 | 0.8182 | 11.7595 | **0.4798** |
| RM | 0.8568 | 0.7342 | 12.6179 | 0.5148 |

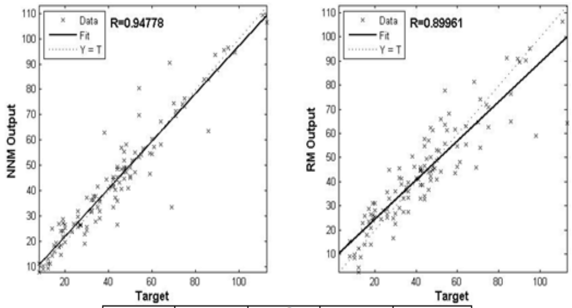



| | R | $R^2$ | RMSE | NRMSE |
|---|---|---|---|---|
| NNM | 0.9209 | 0.8481 | 10.2306 | **0.3993** |
| RM | 0.8619 | 0.7428 | 12.9643 | 0.5060 |

Figure 3. Models: A0000 and A00B1

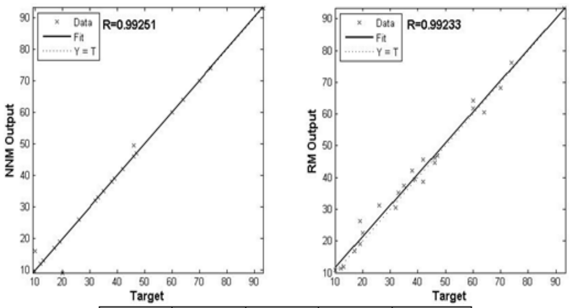



| | R | $R^2$ | RMSE | NRMSE |
|---|---|---|---|---|
| NNM | 0.9396 | 0.8829 | 10.2404 | **0.3813** |
| RM | 0.8983 | 0.8070 | 11.6739 | 0.4347 |

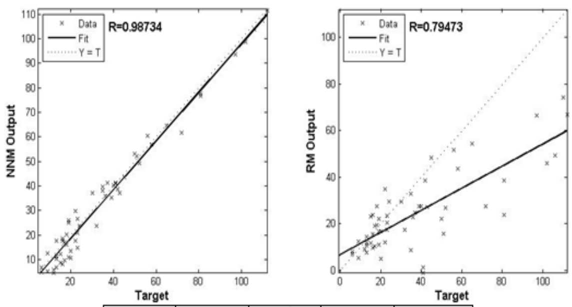



| | R | $R^2$ | RMSE | NRMSE |
|---|---|---|---|---|
| NNM | 0.9478 | 0.8983 | 7.4324 | **0.3212** |
| RM | 0.8996 | 0.8093 | 10.0620 | 0.4348 |

Figure 4. Models: AB101 and AB1C1

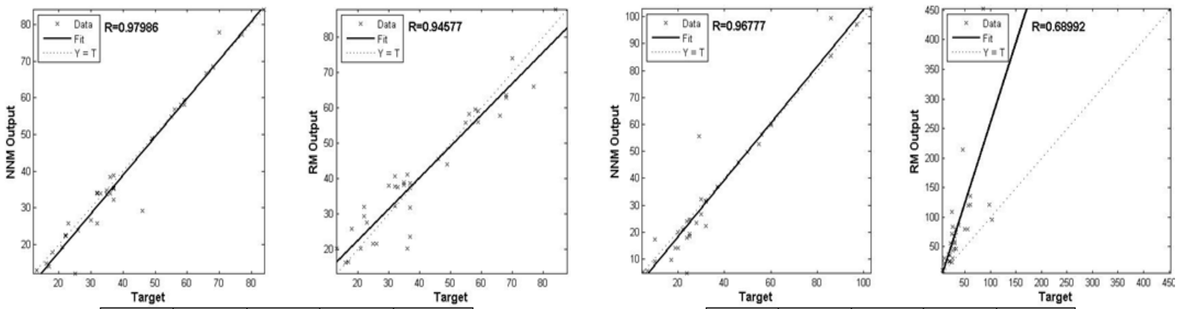



| | R | $R^2$ | RMSE | NRMSE |
|---|---|---|---|---|
| NNM | 0.9925 | 0.9851 | 2.6437 | **0.1213** |
| RM | 0.9923 | 0.9847 | 2.8156 | 0.1291 |




| | R | $R^2$ | RMSE | NRMSE |
|---|---|---|---|---|
| NNM | 0.9873 | 0.9748 | 4.6999 | **0.1664** |
| RM | 0.7947 | 0.6316 | 21.6993 | 0.7684 |

Figure 5. Models: AB102 and AB103




| | R | $R^2$ | RMSE | NRMSE |
|---|---|---|---|---|
| NNM | 0.9799 | 0.9601 | 4.1589 | **0.2226** |
| RM | 0.9458 | 0.8945 | 5.9891 | 0.3206 |

| | R | $R^2$ | RMSE | NRMSE |
|---|---|---|---|---|
| NNM | 0.9678 | 0.9366 | 7.0218 | **0.2789** |
| RM | 0.6899 | 0.4760 | 97.8193 | 3.8854 |

Figure 6. Models: A0004 and A0005

## 5. CONCLUSION

According to the presented results (Figure 3. through Figure 6.), we can conclude that the assumption on the use of a neural network for the production time estimation in relation to a classical robust regression model is justified. For all experimental models (A0000, A00B1, AB1C1, AC102, AB103, A0004, A0005) the applied backpropagation neural network gives better values of key performance indexes (R, $R^2$, RMSE, NRMSE). The biggest difference between the key performance indexes for *NNM* and *RM* estimation models is in the case of model A0005 (input set of 35 data), and lowest in the case of model AC102 (input set of 25 data). The next differences in key performance indexes of individual models ranged from the highest to the lowest values are as follows: AB103, A0004, AB1C1, A00B1 and AC102. The lowest difference between the *NNM* and *RM* estimation model in AC102 (finely machined discs) follows from the nature of the model independent variables and their values that are from a relatively narrow range. The reverse is true for the biggest difference in A0005 (sheets), because of the relatively wide range of independent variables. The key performance indexes in *NNM* estimation models are significantly better than those in all proposed *RM* models, especially in the case of A0005. The reason for this is the proper selection of transfer functions (*tansig* - *tansig* - *purelin*) within the backpropagation neural network layers which provide approximation of linearities and nonlinearities within independent variables, as opposed to the regression model whose approximation is only linear. It should be also noted that the estimation by the *NNM* model would be even better if the experimental data had not been divided in three sets (training set, validating set, and testing set), and thus the estimation made by *NNM* model is based on 70% of the presented data in contrast to the *RM* model where for the obtaining of the regression function all experimental data are always presented.

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